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Tractable Stochastic Unit Commitment for Large Systems During Predictable Hazards

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ABSTRACT Many foreseeable natural hazards, including extreme weather events, lead to an outage of multiple transmission lines. Although such outages can be predicted in advance, there is a great deal of uncertainty in these predictions. To appropriately use the failure estimations in power system scheduling, this paper formulates a stochastic unit commitment (SUC) problem with explicit modeling of the predicted outages. The formulated problem, however, is extremely computationally-demanding, as the uncertainty is placed on the binary status of transmission lines. This paper, then, develops a computationally efficient algorithm to solve the formulated SUC for large-scale systems. The algorithm employs generation shift factors to enable rapid calculation of power flows. Additionally, flow canceling transactions are used to model multiple line outages without having to recalculate shift factors. Finally, critical constraints are iteratively detected and added to the problem. This approach substantially reduces the size of the problem, which helps computational tractability. The effectiveness of the developed algorithm is demonstrated through simulation studies on the Texas 2000-bus test system. The algorithm is used to minimize the lost load during a hypothetical hurricane. The results show that the algorithm is computationally tractable and can effectively identify a preventive dispatch, leading to a substantial reduction in power outages.

INDEX TERMS Extreme weather, Predictable natural hazards, Preventive operation, Power system reliability, Power system resilience, Stochastic unit commitment, Uncertainty management

NOMENCLATURE

SETS

G	Set of generators
g	Index of the generator, $g\epsilon G$
N	Set of buses
n	Index for the bus, $n\epsilon N$
K	Set of transmission lines and transformers
k	Index of the transmission line and transformers, $k\epsilon K$
M	Set of monitored transmission lines and transformers
m	Index of the monitored transmission line, $m\epsilon M$
S	Set of Scenarios
s	Index of the scenario, $s\epsilon S$
O	Set of outages
o	Index of outage, $o\epsilon O$
frm	Set of starting bus of lines
to	Set of ending bus of lines

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PARAMETERS

ng	Number of generation units
nl	Number of transmission lines and transformers
nb	Number of buses
ns	Number of scenarios
c	Cost of generation
c^{NL}	No-load cost for generator
c^{SU}	Start-up cost for generator
c^{SD}	Shut-down cost for generator
c^{lsh}	Load shedding cost (penalty)
c^{og}	Over-generation cost (penalty)
π	Scenario possibility
PG^{max}	Maximum generation power by generator
PG^{min}	Minimum generation power by generator
F^{max}	Maximum thermal capacity of line
Rmp^{HR}	Hourly ramp-up and ramp-down of generator
$\boldsymbol{A}$	Adjacency matrix
$\boldsymbol{B}_{br}$	Branch admittance matrix

$\boldsymbol{B}$	Nodal admittance matrix
b	Susceptance of line
PTDF	Power transfer distribution factor matrix

VARIABLES

$\boldsymbol{F}$	Line flow vector
$\boldsymbol{FC}$	Flow canceling transactions vector
$\boldsymbol{P}$	Net nodal injected power vector
PG	Generated power by a generator
P^d	Power demand at bus
P^{lsh}	Load shedding
P^{og}	Over-generation
u	Unit commitment binary variable
v	Start-up binary variable
x	Shut-down binary variable

I. INTRODUCTION

Short term reliability and economic efficiency in power systems are achieved through scheduling of the available resources. In day-ahead operation, system operators use Unit Commitment (UC) to identify the status and dispatch of the generators [1]. UC, in its extensive form, is a large constrained mixed-integer optimization problem that is computationally burdensome, due to the inclusion of a large number of integer variables, describing the commitment status of the generating units [2]–[4]. Moreover, there are various sources of uncertainties in grid operation, which, if modeled, make the problem even harder to solve. In addition to the number of uncertainties, the source of uncertainty can affect the complexity of the problem as well. For instance, the uncertainty in available renewable energy or load can be modeled by the addition of a random variable, without adding non-linearities to the problem. However, uncertainty in the status of a transmission line would add an uncertain binary parameter to the problem that would substantially add to the complexity of the model. Due to the structure of the problem, uncertain outage of multiple lines is one of the most difficult cases to model in a computationally efficient manner, as power flow calculations will become rather burdensome.

Over the last few years, the damage to the transmission and distribution networks, caused by severe weather, has been the cause of more than 80% of power outages in the United States, affecting many millions of people [5], [6]. Severe weather, such as hurricanes, tornados, and ice storms, usually leads to the outage of multiple transmission and distribution elements, whose failure probabilities can be predicted. However, as the number of the affected elements is large and the outages change the network topology over time, inclusion of such probabilities within the UC problem will make it extremely hard to solve using existing formulations. This paper offers a solution to this challenge by developing a computationally tractable model for solving the unit commitment problem, in the presence of predictable but uncertain possibility of multiple line outages.

There are two main challenges for achieving tractability: (i) the lack of efficient formulation that can handle simultaneous outage of more than one line; and (ii) the computational burden of implementation for large real-world networks. Although the recent literature, as will be discussed later in this section, offers some interesting insights, relevant to this problem, these two challenges have remained unresolved. This paper contributes to the literature by developing a method that can effectively overcome both of these barriers.

Traditionally, deterministic methods based on the operating reserve requirements have been used to solve the unit commitment problem in the presence of uncertainties. In deterministic methods, a minimum level of reserve is obtained for uncertainty management [7]. Although the deterministic techniques are computationally efficient, they do not necessarily guarantee reliability and can be relatively economically inefficient. Moreover, the current industry practices focus on *N*-1 reliability and are neither designed nor capable of handling multiple line outages. It should be noted that with the current deterministic reserve requirements, reserve deliverability is not guaranteed even for an *N*-1 event [8]. An alternative approach to deterministic methods is stochastic optimization. A scenario-based stochastic optimization problem models future uncertainties through a number of scenarios, each of which with a realization probability. As stochastic optimization explicitly models uncertainties, it can achieve higher levels of reliability and economic efficiency. This improvement in solution quality, however, comes at the cost of substantial computational burden [1], [9]–[11]. Since the introduction of stochastic unit commitment (SUC), many researchers have developed a variety of methods to model more uncertainties and improve SUC's computational efficiency [12]–[16]. The computational demands of the problem can vary based on the type of uncertainty, e.g., generation dispatch or transmission status, and the uncertainty distribution, e.g., normal or Boolean. As mentioned earlier, this paper focuses on the uncertainty associated with the status of transmission elements.

In addressing the multiple equipment failures, the majority of existing studies are focused on generation unit failures, as *N*-*k* security-constrained UC, where k can only be generation units [17]–[19]. The literature on modeling *N*-*k* generation outage scenarios completely abstracts from the complexities of transmission network and power flow calculations [17]–[19]. There is also a vast body of literature focusing on uncertainties regarding the error in the prediction of power injection by renewable energy resources [20]–[28]. There are a few studies on the modeling of uncertain equipment failures in the transmission network. A method to solve the security-constrained UC for large networks with one line outage possibility is developed in [29]. However, the proposed method is not valid when there are multiple line outages. Another relevant work in terms of the formulation is the transmission topology optimization problem [30], where a number of transmission lines can be switched out. We adopt this technique in our paper to improve the computational efficiency of our model. Another important observation in the literature is presented in [31], where the authors suggest that combining stochastic methods with deterministic methods is advantageous as the deterministic methods can compensate for the unseen uncertainties. Although this approach will enhance the solution time, the problem can still be too hard to solve even with a few scenarios.

The main contribution of this paper is developing a computationally efficient stochastic unit commitment formulation, which can handle multiple uncertain but predictable line outages. This is achieved through the adoption of flow canceling transactions [30], which enables fast calculation of power flows even in the presence of multiple line outages. The second contribution is the employment of an iterative approach for identification of critical constraints, which enables the elimination of a large number of variables and constraints from the model, and, thus, helps tractability. The final model is able to effectively solve SUC during severe weather for real-world large power systems. The solution leads to lower levels of a power outage as the damage to the network is explicitly modeled. The calculated dispatch is expected to rely less on the transmission elements that are likely to fail, resulting in higher levels of security and reliability.

The remainder of this paper is organized as follows: Section II presents the modeling techniques that are used in this paper to achieve computational efficiency. In Section III, the algorithm and developed model are described, and the mathematical formulation of the problem is presented. A simulation study, used to evaluate the performance and accuracy of the developed model, is discussed in Section IV. Finally, Section V presents the conclusions of this study and opportunities for future research.

II. MODELING TECHNIQUES

In this section, in order to make the formulation easier to follow, this section presents two modeling techniques that are used for fast computation of power flows: shift factors and flow canceling transactions. A combination of these two methods enables quick power flow calculations both for the base case and post *N-k* line outage.

A. POWER FLOW MODELING

Almost every single system operator in North America uses one or another form of DC optimal power flow in its operation software [32]. While the DC-based, B-θ formulation is well-known in academic studies as described in [32]–[34], we decided not to use it due to its computational inefficiency. The B-θ formulation needs to calculate the voltage angles for all the buses and all the hours individually to calculate the line flows. This translates to a large number of unnecessary variables and constraints in the model that leads to an increased computational burden.

The *injection shift factor* and *power transfer distribution factor* (PTDF) are sensitivity factors, which help avoid unnecessary calculations, and thus, are widely adopted by the industry [30], [35]. Injection shift factors determine the sensitivity of the line flows with respect to nodal power injections. PTDFs represent the sensitivity of line flows with respect to a transfer of power between two buses. The net power injection at each bus can be assumed as a transfer from that bus to the slack bus. Therefore, PTDFs can be used to determine the line flows when the slack bus is excluded, and all the other nodal injections are known. Note that the PTDF matrix is a network describer, and is independent of the operation point. As long as the network topology does not change, PTDF needs to be calculated only once.

If the net injection value is known at all buses, it is possible to calculate the line flow by using the **PTDF** matrix. This is formulated as follows:

$$\boldsymbol{F} = \boldsymbol{PTDF} \times \boldsymbol{P}, \tag{1}$$

where $\boldsymbol{P}$ is the net nodal power injection vector, which equals nodal generation minus nodal load, excluding the slack bus. In a simple case with no load shedding or over-generation, net nodal power injection can be calculated as:

$$P_{(n)} = PG_{(n)} - P^{d}_{(n)}.n \quad \forall \neq \text{Slack bus} \tag{2}$$

The **PTDF** matrix, which is an $nl\times(nb\text{-}1)$ matrix, is calculated as:

$$\boldsymbol{PTDF} = \boldsymbol{B}_{br}\boldsymbol{A}\boldsymbol{B}^{-1}, \tag{3}$$

where $\boldsymbol{B}_{br}$ is an $nl\times nl$ matrix and calculated as:

$$B_{br(k,k')} = \begin{cases} b_{(k)}, & k = k' \\ 0, & k \neq k' \end{cases} \qquad \forall k, k' \in \mathrm{L} \tag{4}$$

In $\boldsymbol{B}_{br}$, the diagonal elements are lines susceptances, and all non-diagonal elements are zero. $\boldsymbol{A}$ is an $nl\times(nb\text{-}1)$ adjacency matrix, and its elements are determined as:

$$A(k,n) = \begin{cases} +1, & \text{if line } m \text{ starts from node} \quad \forall l, \text{ and } \forall\, n \\ -1, & \text{if line } m \text{ ends at node } n \quad \neq \text{ Slack bus} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

B is an $(nb\text{-}1)\times(nb\text{-}1)$ admittance matrix (slack bus is excluded), and its elements are calculated as:

$$B_{(n,n')} = \begin{cases} -b_{(n,n')}, & n \neq n' \\ \sum_{n'=1}^{nb} b_{(n,n')}, & n = n' \end{cases} \tag{6}$$

It is worth mentioning that in the same way that (1) calculates the power flow for all lines, power flow of line k can be calculated as:

$$F_{(k)} = \boldsymbol{PTDF}_{(k)} \times \boldsymbol{P} \quad \forall k \tag{7}$$

B. MULTIPLE LINE OUTAGE MODELING

In the standard PTDF method, a change in the network topology requires recalculation of the PTDF matrix. To demonstrate that how much time calculation of PTDF requires, in our results for large-scale networks, PTDF calculation consumes around 40% of total solution time when the model solves the standard unit commitment problem, with no uncertainty modeling, for 24 periods. The calculation times are shown later in Section IV. Thus, in SUC developed in this paper, as the network topology can change any time, it is not efficient to recalculate the PTDF. A single line outage can be handled simply by using the famous *line outage distribution factors* (LODF) [36]. Numerous studies use this technique to calculate the power flow with different applications with a single line outage [37], [38]. However, this standard formulation is not valid in the case of multiple line outages.

Flow canceling transactions are introduced in [30] for network topology optimization problems. Here, we employ the same concept to model multiple line outages. Flow canceling transactions are a pair of injections that would represent the outage of a line. The transactions are calculated such that their impact on the rest of the network resembles the outage of the line. Fig. 1 shows a meshed network with two lines that are out: O_1 and O_2. The outage of these lines is represented by a pair of flow canceling transactions: FC_1 and FC_2. Additionally, Fig. 1 shows another line in the meshed network, line m, whose flow is affected by outage of other lines.

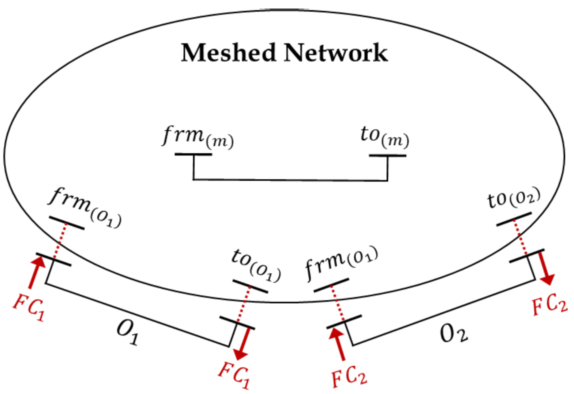

FIGURE 1. Flow canceling transactions to represent multiple line outages.

To clearly explain how flow canceling transactions are calculated, we assume that the transactions are placed on two fictional buses that are infinitely close to the ''from'' and ''to'' buses of the lines experiencing an outage. The connection between the real buses and the fictional buses are shown with dotted lines. If the flow on these dotted connections is zero, the lines will be effectively out, from the viewpoint of the rest of the network. This flow will include the original line flow as well as the impact of the flow canceling transactions. The original flow on the line can be calculated using the PTDF matrix and the nodal injections:

$$F_O = \boldsymbol{PTDF}_{(O)} \times \boldsymbol{P} \tag{8}$$

The impact of flow canceling transactions on the line flow can also be calculated using the PTDF matrix:

$$\left(1 - \left(PTDF_{O,frm_{(O)}} - PTDF_{O,to_{(O)}}\right)\right) FC_O \tag{9}$$

Note that $(PTDF_{O,frm_{(O)}} - PTDF_{O,to_{(O)}})$ portion of the transaction will flow on the line itself and $(1 - (PTDF_{O,frm_{(O)}} - PTDF_{O,to_{(O)}}))$ of it will flow through the meshed network. This portion of the flow has to pass the dotted connections. Thus, to model a line outage, FC_O should be calculated in a way that the total flow on the dotted portion of the line becomes zero:

$$\boldsymbol{PTDF}_{(O)} \times \boldsymbol{P} \left(1 - \left(PTDF_{O,frm_{(O)}} - PTDF_{O,to_{(O)}}\right)\right) FC_O = 0 \tag{10}$$

To extend this equation to the case of multiple line outages, the impact of flow canceling transactions on all the open lines should be included in the calculation of the flow canceling transactions. This will lead to a system of $|O|$ linear equations and $|O|$ unknowns, as will be used later in (20). This is key because the flow canceling transactions will not add nonlinearities to the model. It should be noted that flow canceling transactions are valid as long as the outages do not isolate a meshed part of the network. To ensure the validity of the model, the outage possibilities, and their impacts on the meshed network topology are checked in the model.

III. FORMULATION AND ALGORITHM

The main goal here is to minimize the generation cost plus the penalty associated with load shedding and over-generation, in the presence of uncertain multiple line failure scenarios during the day. Load shedding follows the shortage of generation or disconnection of load from the network. Note that load may still be connected to the grid, even after outage of multiple lines, but the transfer capacity is reduced below what load demands. Similarly, after disconnection of a sizeable load, due to the sudden reduction in demand and the ramp-down limitations of generators, the network experiences over-generation. Another condition that leads to over-generation is full or partial disconnection of an operational generation unit.

As discussed earlier, for this application, deterministic methods are not efficient in terms of economic efficiency and reliability. A simple robust optimization, where the worst case is identified and solved, [39]–[41] may also be inefficient due to two main shortcomings. First, it is not easy to determine the worst-case when there are multiple outages. In other words, it is not necessarily a correct assumption that any line with any chance of failure should be considered faulty to create the worst possible case. For example, if there are two parallel lines with failure chances, losing both may be better than losing only the stronger one, in terms of congestion and transfer capability. Second, even if the worst case is efficiently computable, exclusively considering such cases may impose unnecessary costs through tighter constraints to the system. It should be mentioned that the robust optimization as minimization of maximums may be promising for this problem, but as the number of possible futures is extremely large, the problem may become computationally intractable. Based on some of the advantages described in [9], particularly the fact that multiple scenarios can be explicitly modeled in stochastic optimization, the model developed in this paper is based on stochastic unit commitment.

A. ALGORITHM

For large networks, the mathematical representation of SUC will include too many variables and constraints. A properly designed formulation should reduce the required calculation by avoiding a large number of unnecessary variables and constraints without changing the underlying problem. This paper aims to offer a highly efficient formulation that avoids unnecessary calculations using an iterative approach by only including the necessary variables and constraints.

To do so, the main calculations of SUC are divided into three segments, as shown in Fig. 2 In the first segment, block A reads the data from stored files, and block B calculates network parameters that will not be changed over the course of the study. The stored files include information on buses, lines, loads, generators, outages, and failure scenarios. The main network parameters that will not change over time include the **PTDF**. At the end of this segment, the parameters that define the constraints are set for the first iteration of SUC to exclude all the line thermal capacity limits and generation ramp constraints.

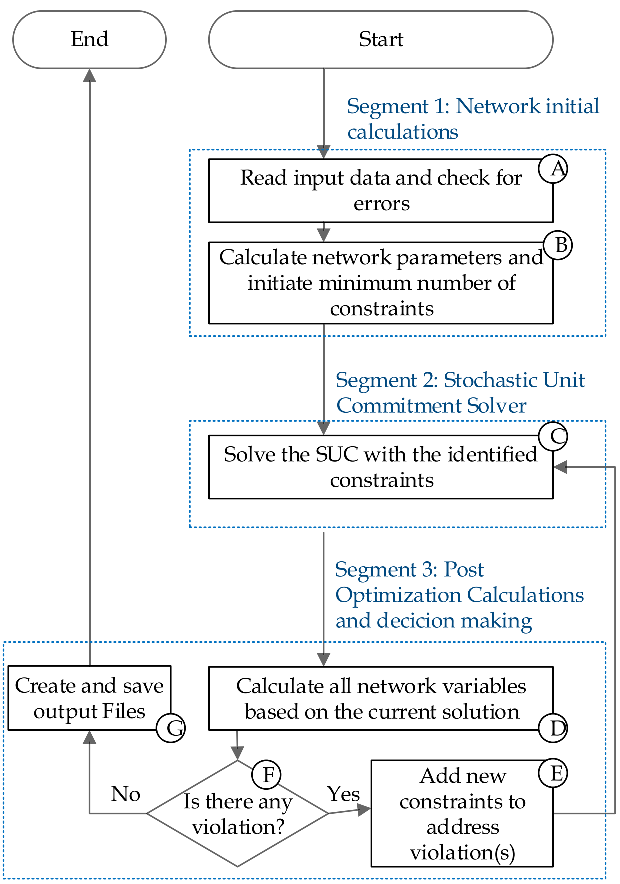

FIGURE 2. Simplified flowchart of calculations.

At the beginning of the second segment, block C reads control flags and generates constraints for the current iteration of the SUC, based on these flags. Note that the flags are all initialized to 0 for thermal and ramping constraints, at the end of segment 1. These flags indicate the constraint/variable that should or should not be added. For example, $M_{(s)}$ is a control matrix that includes all the lines that should be monitored under scenario s, and $O_{(s)}$ reflects the failed lines under scenario s.

Finally, in the third segment, with the calculated solution from segment two, all network variables are calculated in block D, and block E and F check if the values are out of bound and any more constraints are needed to be added to the SUC in the next iteration. If the optimal solution is found and no constraint is violated, block G creates the output results.

This approach essentially removes a large number of unnecessary variables and constraints from the optimization model. The variables are calculated, and the constraints are checked only after a solution is found. In the case that the solution violates any constraint, the constraint is added in the next iteration. Since optimization is much more computationally burdensome compared to post-optimization processing, this approach significantly reduces the computational burden of the problem, compared to solving a single iteration that includes all the constraints.

B. FORMULATION

Objective Function: The objective function, for most cases can be defined as the minimization of the cost function. However, in applications such as preventive operation, the goal is to minimize the lost load during a predictable hazard, putting reliability above the cost. Hence, the objective function can be defined as the minimization of load shedding plus over-generation. One way to balance economic efficiency and reliability is to add the value of lost load to the generation dispatch cost, as shown in:

$$\begin{aligned} Minimize\,\Sigma_s\{\pi_{(s)}\Sigma_t[\Sigma_g(c_{(g)}PG_{(s,g,t)} + c^{NL}_{(g)}u_{(s,g,t)} \\ + c^{SU}_{(g)}v_{(s,g,t)} + c^{SD}_{(g)}x_{(s,g,t)}) \\ +\Sigma_n\left(c^{lsh}_{(n)}P^{lsh}_{(s,n,t)}\right) + \Sigma_g(c^{og}_{(g)}P^{og}_{(s,g,t)})]\} \end{aligned} \tag{11}$$

In (11), the first term represents generation cost; the second term represents load shedding cost; and the third term represents over-generation cost. For simplicity, this is shown in (12).

$$\begin{aligned} Minimize\,\Sigma_s\{\pi_{(s)}\Sigma_t[\Sigma_g(Generation\ cost) \\ + \Sigma_n(Load\ shedding\ cost) + \Sigma_g(Over\ Generation\ cost]\} \end{aligned} \tag{12}$$

The generation cost itself includes power generation cost, no-load cost, start-up cost, and shut-down cost. The load shedding is modeled as an expensive generator that is installed at all buses that have load. The over-generation is defined as a load with expensive penalty cost installed at each generating node. Note that by removing the first term in (11) and ignoring penalty cost indices, the objective function will be the minimization of load shedding and over-generation only.

Constraints: The constraints of the problem are the following:

$$PG_{(g)}^{min} u_{(s,g,t)} \leq PG_{(s,g,t)} \leq PG_{(g)}^{max} u_{(s,g,t)} \quad \forall s, g, t \tag{13}$$

$$\sum_{h=t-UT_g-1}^{t} v_{(s,g,h)} \leq u_{(s,g,t)} \quad \forall s, g, t \tag{14}$$

$$\sum_{h=t-DT_g-1}^{t} x_{(s,g,h)} \leq 1 - u_{(s,g,t)} \quad \forall s, g, t \tag{15}$$

$$v_{(s,g,t)} - x_{(s,g,t)} = u_{(s,g,t)} - u_{(s,g,t-1)} \quad \forall s, g, t \tag{16}$$

$$P_{(s,n,t)} = \left[PG_{(s,n,t)} + P_{(s,n,t)}^{lsh}\right] - \left[P_{(s,n,t)}^{d} + P_{(s,n,t)}^{og}\right] \quad \forall s, n, t \tag{17}$$

$$-F_{(m)}^{max} \leq F_{(s,m,t)} \leq F_{(m)}^{max} \forall s, t \quad and\ \forall m \in \mathrm{M}_{(s)} \tag{18}$$

$$F_{(s,m,t)} = (\boldsymbol{PTDF}_{(m)} \times \boldsymbol{P}_{(s,t)}) + \sum\nolimits_{o \in O(s,t)} \left(PTDF_{(m,frm_{(o)})} - (PTDF_{(m,to_{(o)})}\right) \times FC_{(s,t,o)} \quad \forall s, t \quad and\ \forall m \in \mathrm{M}_{(s)} \tag{19}$$

$$(\boldsymbol{PTDF}_{(o)} \times \boldsymbol{P}_{(s,t)}) - FC_{(s,t,o)} + \sum\nolimits_{o' \in O(s,t)} \left(PTDF_{\left(o,frm_{(o')}\right)} - (PTDF_{\left(o,to_{(o')}\right)})\right) \times FC_{(s,t,o')} = 0 \quad \forall s, t \quad and\ \forall o \in \mathrm{O}_{(s,t)} \tag{20}$$

$$\sum\nolimits_{n} [(PG_{(s,n,t)} + P_{(s,n,t)}^{lsh}) - P_{(s,n,t)}^{d} + P_{(s,n,t)}^{og}] = 0 \quad \forall s, t \tag{21}$$

$$Rmp_{(g)}^{HR} u_{(s,g,t-1)} + PG_{(g)}^{max} v_{(s,g,t)} \geq PG_{(s,g,t)} - PG_{(s,g,t-1)} \quad \forall s, g, t \tag{22}$$

$$Rmp_{(g)}^{HR} u_{(s,g,t)} + PG_{(g)}^{max} x_{(s,g,t)} \geq PG_{(s,g,t-1)} - PG_{(s,g,t)} \quad \forall s, g, t \tag{23}$$

$$0 < P_{(s,n,t)}^{lsh} < P_{(s,n,t)}^{d} \quad \forall s, n, t \tag{24}$$

$$0 < P_{(s,n,t)}^{og} < PG_{(g)}^{max} \quad \forall s, n, t \tag{25}$$

$$u_{(s,g,t)} = u_{(s',g,t)} \forall s, \quad s' \in S \tag{26}$$

Generation maximum and minimum limits are represented in (13). Minimum up and down times are given in (14)-(16). (17) represents the nodal net injected power calculation. It should be mentioned that (17) is the comprehensive form of (2) when load shedding and over-generation are allowed. Load shedding and over-generation are modeled as injections and withdrawals, respectively. (18) ensures that the flow on the lines that should be monitored (those that violated their thermal capacity in the previous iteration) stay within limits; (19) and (20) calculate the line power flow for such lines. (19) and (20) account for the changes in the topology of the network, using flow canceling transactions, as described in Section II.

The advantage of (20) is that it represents the impacts of multiple line outages with a system of linear equations. Adding these equations to the optimization problem as constraints will model simultaneous outages while keeping the complexity of the problem to a linear program. This way, the flow canceling transactions are calculated within the optimization problem, which makes the calculation of flow on other lines, e.g., line m, rather simple. For any other line in the network, the flow canceling transactions are treated simply as nodal injections, as shown in (19).

The power balance is defined in (21), allowing load shedding and over-generation. (22) and (23) represent the ramp-up and ramp-down limitations over the generation units. (24) enforces the maximum value of non-negative load shedding to be less than planned load at each bus, and (25) limits the non-negative value of over-generation corresponding to each generation unit to be less than maximum generation power of the same unit. The last equation, (26), enforces the commitment status of generation units to be the same for all scenarios. Equations (11) to (24) are used in the second segment of the flowchart, shown in Fig. 2.

Post-optimization calculations in Segment 3: In segment three of the flowchart, the same equations as segment two are used with one change. In this segment, all the network variables are calculated, not just the previously selected ones. For example, in power flow calculation, equations (18) and (19) are changed to (27) and (28), respectively.

$$-F_{(k)}^{max} \leq F_{(s,k,t)} \leq F_{(k)}^{max} \quad \forall s, t, k \tag{27}$$

$$F_{(s,k,t)} = (\boldsymbol{PTDF}_{(k)} \times \boldsymbol{P}_{(s,t)}) + \sum\nolimits_{out(s,t)} \left(PTDF_{(k,frm_{(out)})} - (PTDF_{(k,to_{(out)})}\right) \times FC_{(s,t,out)} \quad \forall s, t, k \tag{28}$$

This change guarantees that network violations are detected, and necessary changes are implemented before algorithm termination. Please note that the flow canceling transactions in (28) is constant, as they have already been calculated as the solution to the optimization problem. If a violation is found, the constraint controller matrices, such as M, will be updated. This update will change the optimization model, by adding additional constraints, in the next iteration and eliminate the detected violations. If no violation is found, the calculated values will be saved as the final solution to the SUC problem.

IV. TEST CASE

To evaluate the performance and validate the accuracy of the proposed model, it is first compared with two standard unit-commitment methods on a large network. The reason that we do not compare them in solving the SUC is that we were not able to solve any large network with multiple scenarios using other methods, with the hardware that was available to us and within an acceptable time. The selected test case network is

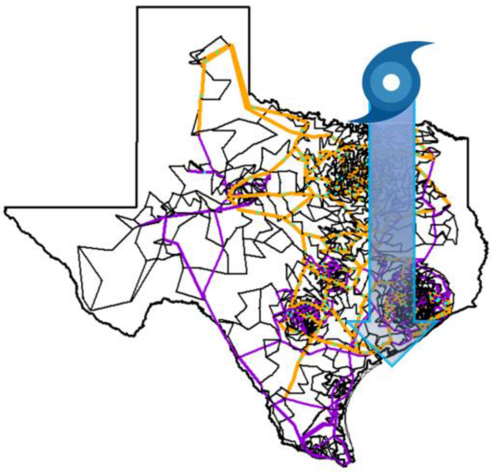

FIGURE 3. Location of transmission lines and the hurricane path in the Texas 2000-bus system. Line color indicates voltage level and hurricane path is shown with an arrow that moves across the network within 10 hours.

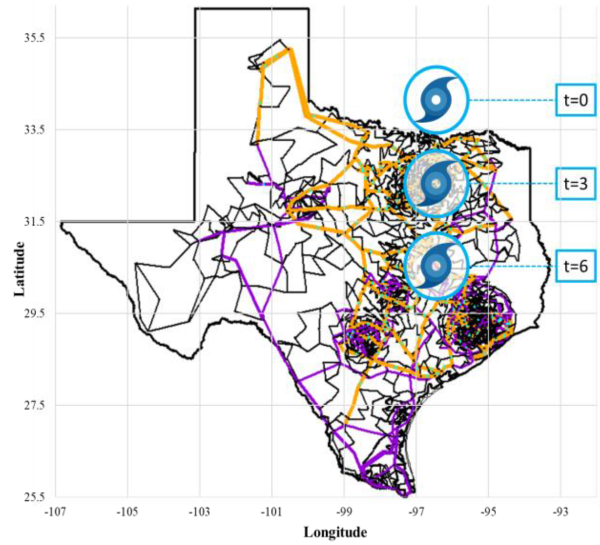

FIGURE 4. Discretized hurricane path: this figure shows the method that is used to determine the failure chance of each transmission line as the hurricane moves. At each hour, transmission lines, located within the effective radius of the hurricane, are analyzed for potential damage. Three representative hours are shown in this figure: 0 (hr), 3 (hr), and 6 (hr).

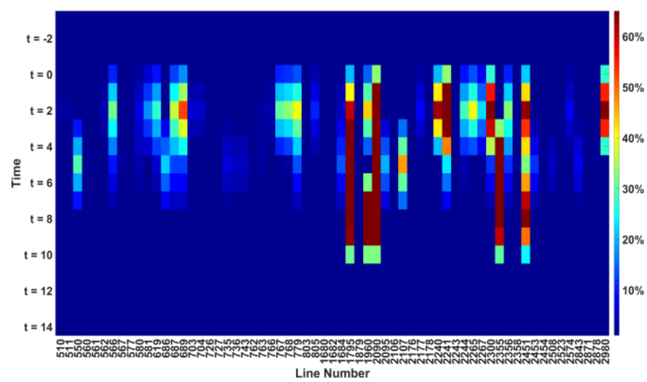

FIGURE 5. Temporal failure chance of affected transmission lines when the hurricane is predicted to hit the network.

ACTIVSg2000 (Synthetic grid on a footprint of Texas) with 2,000 buses, 540 generation units, and 3,206 transmission lines [42]. As a source of uncertainty, we used the data regarding the effect of a hurricane on the transmission lines. As the hurricane hits different parts of the network at different times, each element of the network there has a failure possibility, which is a function of time. The test system alongside the path for the hurricane is illustrated in Fig. 3.

A. PROBABILISTIC MODEL OF LINE OUTAGES

In order to determine the probabilistic model for line outages according to the selected hurricane and its characteristics and path, the study time is discretized with a resolution of hours. Temporal location of the center of hurricane and its effective radius from the center is then calculated as is shown in Fig. 4, for three selected times. Affected lines at each time step are determined and failure chance for each line is calculated based on the characteristic of the line, and how far it is from the hurricane center. Note that if any point between start-bus and end-bus of line is affected by the hurricane, the entire transmission line has a chance of failure.

The hurricane we modeled as a test case hits the first element of the network at time zero and fades out after 10 hours. Calculation results for the temporal failure chance of the affected lines are shown in Fig. 5.

B. SCENARIO SELECTION METHOD

The calculated failure prediction as described in the previous part, is used to generate a scenario set. Considering the many numbers of uncertainties (line outages), 63 lines, the total number of possible scenarios is more than 4E+65. This is calculated by using (29) and assuming that if any line failed at any time, it would not be fixed within the horizon of study.

$$NS = (T+1)^{N_e} \tag{29}$$

In (29), NS, T and N_e are total number of possible scenarios, number of time steps, and number of element with uncertain failure possibilities, respectively. Obviously, it is not possible to evaluate all scenarios by modeling them in SUC problem. By taking into account the complexity of the formulation and required hardware, a sufficient set of scenarios, should not include more than 20 for the network size as big as our test case with 3,206 lines, with reasonably powerful hardware. After evaluating different sized scenarios sets, we suggest that 10 scenarios in most cases can provide enough accuracy while maintaining the calculation time within an acceptable range. One of the most efficient methods designed especially for this application is called Multidimensional Scenario Selection method (MDSS) [42]. In this method, uncertainties are sorted based on their different characteristics such as failure chance and their importance to the network, and then by considering thresholds on each aspect of the characteristic. Hence, each scenario will define a set of threshold values. By comparing the temporal value of each characteristic with the corresponding threshold value, scenarios are created. This procedure is done for every uncertainty and every scenario. The resulting scenario set is created in a way that the first scenario represents the best possible case (no outage), and the last scenario represents the worst possible case in terms of outages, and the rest in between. Interested individuals can refer to [43] where MDSS is explained with details.

C. SIMULATION ENVIRONMENT

While there are a number of appropriate software environment options, we chose to use Java in combination with IBM CPLEX as our simulation environment. Java is fast and offers flexible memory management [43], [44]. The machine we used to run the methods utilizes Intel® Core™i7-7700 CPU @3.60GHz as a central and only processor combined with 16.0 GB of RAM, which is configured as dual-channel bandwidth @ 2.40 GHz. The software package includes Eclipse Jee ver. 4.1 and IBM CPLEX ver. 12.8-64 bit running on Windows 10 Pro.

D. NUMERICAL RESULTS

TABLE 1 presents the results obtained for the standard UC problem when over-generation and load shedding are not allowed, and there is no outage during the period of study. In this table, B-θ represents the standard B-θ UC formulation; PTDF represents the fully constrained PTDF UC with all the network constraints included.

TABLE 1. Benchmark result for the proposed method.

	Expected Unserved Load (MWhr)	Expected Cost ($)
Business as Usual	39,393	1.190 E+9
Preventive SUC	17,188	0.531 E+9

As can be seen in **TABLE 1**, the proposed algorithm has the same accuracy as other methods while it needs much less memory and time. Here, a slight difference in objective value is due to the MIP gap in CPLEX, which is set to 0.05. It should be mentioned that while the proposed method needs a total time of 2 minutes to solve the problem, 45 seconds of this time is consumed by the calculation of PTDF matrix.

The main reason for the reduced calculation time is the handling of transmission constraints. The number of line constraints is decreased by 99.06% in the proposed method, as there are just 30 lines that violate the thermal capacity, not all 3,206 lines.

Adding load shedding and over-generation to the model significantly increases the number of variables and constraints for the generation units, which itself increases the solution time. It should be mentioned that the calculation time is affected by the penalty cost considered for load shedding and over-generation. For a penalty cost of 1,000 times more than the most expensive generated unit of power (about \$30,000 MWhr^{-1}), the solution time increases to 4 minutes. The results for the same case as shown in **TABLE 1**, as well as load shedding and over-generation are shown in **TABLE 2**. As can be seen, the objective value is the same while the calculation time doubled.

TABLE 2. Comparison between standard UC and when load shedding and over-generation are allowed at a high cost.

	Objective Value ($)	Unserved Load (MW)	Solution Time (Sec)	Iterations Required
Standard UC	2.0185E+7	0	120	3
UC + Load shedding and Over-Generation	2.0185E+7	0	250	4

Finally, adding scenarios to the stochastic UC is evaluated in the next step. In order to test the stochastic UC performance, we considered ten scenarios as discussed previously. Ten scenarios describe ten possible futures regarding the uncertainties in the network.

Having this test case, we aim to investigate two research questions: 1) is the algorithm computationally efficient? and 2) does it significantly improve reliability?

In term of performance of the calculations, the solution time is about four hours, and it consumes less than Five GB of RAM (system memory), while there is more free available memory on the system. An important note here is that as the algorithm uses an iterative method to detect bounded variables and put them in the constraints, the solution time and memory is highly dependent on outages (number of outages and their locations and times) and scenarios. We tried different cases from a few outages to many outages with different scenario creation methods. While the solution time was different for each case, it was never more than ten hours for ten scenarios. This confirms that the method developed in this paper is tractable for large scale systems.

To answer the second question, the SUC problem is solved with two methods: 1- no possible outage/uncertainty is considered, and 2- outage predictions are included in the SUC problem and the proposed method is used. Then, we ran Monte Carlo simulations, using the failure possibility data we had from the hurricane, to check how effective the resulting solution is. For each realization through the Monte Carlo process, one possible future for the system by considering the outage data, as shown in Fig. 5 is implemented into the model. As the commitment variables are assumed to be the first-stage variables, the commitment of the generation unit cannot change unless the generation unit is disconnected from the network. In case when the generation unit is disconnected, a minimum time to shut down the unit is applied, and the equivalent over-generation value is calculated and added to the solution. After running thousands of realizations, the results are calculated and shown in **TABLE 3**.

A significant finding here is that preventive SUC can reduce the expected unserved load by 56.4%. Under substantial disturbances such as hurricanes, reducing power outages

TABLE 3. Comparison between business as usual and using preventive SUC for day-ahead generation plan.

	Expected Unserved Load (MWhr)	Expected Cost ($)
Business as Usual	39,393	1.190 E+9
Preventive SUC	17,188	0.531 E+9

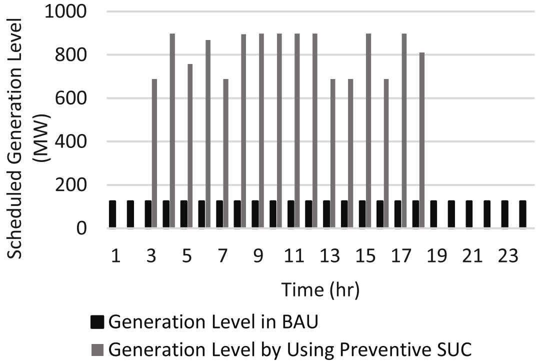

FIGURE 6. Scheduled generation level for generation unit #530, when preventive SUC is used and when not used (BAU).

by a factor of 50% is rather significant. Note that such reduction in outages was achieved only by an enhanced implementation of SUC over the existing operation tolls, with no system hardening.

Using preventive SUC changes the generation day-ahead schedules by preparing the generation units for possible disconnection of loads and other generators at different times and locations. As an example, generation unit #530 has rapid ramp-up and ramp-down values, with relatively expensive generation cost, and is located where the connection line predicted to be stable during the hurricane impact. In BAU, this generation is scheduled to produce power at a constant rate near its = minimum capacity. However, after adding uncertainties to the model, and considering possible outages of other generation units, this unit will be scheduled at dynamic rates from its minimum to its maximum generation level, with sometimes even being turned off. This is shown in Fig 6.

As the objective function in preventive SUC covers both load shedding (plus over-generation) and generation cost, it is also expected that the scheduling stays similar to BAU with some exceptions (like generator #530) that compensate for the damages to the transmission network. Fig. 7 demonstrates the total daily scheduled generated power for each generation unit (those that are not offline all-day), when preventive SUC is used. Fig. 7 also includes (orange bars) the difference in daily generation of each unit, between when preventive SUC is used and when BAU is used to solve the unit commitment problem. It can be seen that in most cases, the total daily generation will be the same for most generation units. Three hundred seventy-seven out of all the 544 generation units have the same daily generated energy (216 of them are set to be offline for the day and are not included in Fig. 7).

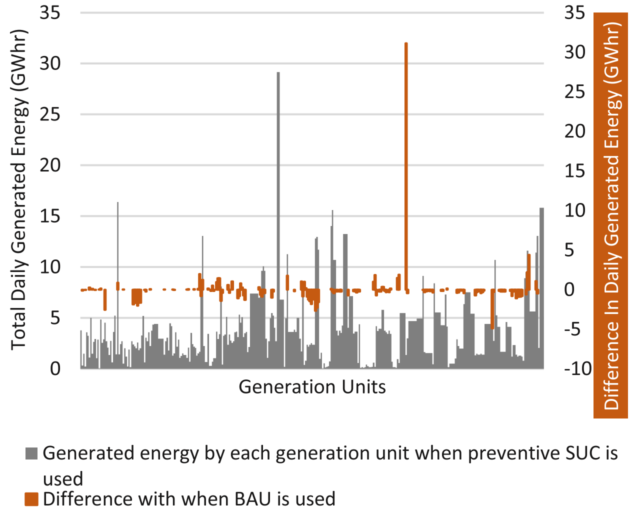

FIGURE 7. Changes over generated energy by each generation units when preventive SUC is implemented in comparison with BAU.

Total shifted generated power from one generator to the other is 127 GWhr, which is around 10% of the total scheduled generated energy of 1,302 GWhr.

V. CONCLUSION

There is no existing method to handle uncertain but predictable *N-k* line outages in a stochastic unit commitment, in a computationally efficient manner. This paper, for the first time, develops a tractable method to solve SUC, in the presence of the likely failure of a large number of transmission lines. The method uses shift factors for rapid calculation of power flows and flow canceling transactions for efficient modeling of multiple line outages. Additionally, to keep the size of the problem manageable, critical constraints are detected and added iteratively. As one application for the proposed algorithm, a preventive day-ahead unit commitment model was developed for Texas 2000-bus test system, affected by a hypothetical hurricane. The simulation results showed that it is possible to reduce the power outage and increase system reliability significantly by implementing the proposed method. The results also showed that the proposed method is tractable on large-scale systems.

FUTURE WORK

To effectively use and solve preventive SUC, there are two main challenges that need to be addressed. First, a tractable method and formulation are required to handle large-scale real-world systems. Second, an efficient scenario selection method is needed to select a small but representative subset out of all the possible scenarios. In applications such as preventive SUC, to minimize the lost load during a hurricane, the number of all possible scenarios can easily be larger than the number of atoms in the earth. Obviously, all of the scenarios cannot be modeled. The first challenge was addressed in this paper; the second challenge requires further research in the future.

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